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Centrality-Based Caching for Mobile Wireless Networks

Ejder Baştug[◇], Kenza Hamidouche[◇], Walid Saad^{*} and Merouane Debbah[◇]

[◇]Alcatel-Lucent Chair - SUPÉLEC, Gif-sur-Yvette, France

^{*}Wireless@VT, Bradley Department of Electrical and Computer Engineering, Virginia Tech, USA
{ejder.bastug, kenza.hamidouche, merouane.debbah}@supelec.fr, walids@vt.edu

I. EXTENDED ABSTRACT

The introduction of anticipatory, proactive caching mechanisms that store popular content at user terminals and base stations is emerging as an integral component of the next-generation, 5G, cellular networks [1], [2]. In essence, endowing cellular networks with the ability to cache users' content at the network's edge provides an effective means for offloading traffic from the resource-constrained network infrastructure while reducing access delays to requested content. However, developing efficient caching mechanisms for cellular systems raises important questions such as *what*, *where* and *when* to cache under given perfect or imperfect "statistics" are still under investigation (see [3]–[5] for a brief literature).

In recent years, the social networks such as Facebook, Twitter, LinkedIn have become one of the major contributors to mobile data traffic with their network share is expected to increase in upcoming years. Social networking data and social content dissemination provide a key opportunity that can be exploited for optimizing the use of content caching in wireless cellular networks and reducing the traffic load over the network's backhaul infrastructure. However, privacy and security concerns may present an important barrier that prevents network operators from efficiently exploring social data in their resource allocation mechanisms. To overcome this barrier, in this short abstract, we propose a novel caching approach that exploits the fact that, although the information on content dissemination in social networks (evolution of content popularity profile) may not be known, the social network structure can be readily explored for optimized caching at small base stations (SBSs).

One key measure of *influence* in a social network is the so-called notion of *centrality* which allows to pinpoint important and influential nodes within a social structure [6]. Although the idea of using centrality measures for caching decision in the context of information centric networks has been explored in some existing works such as [7], our scenario is indeed different. In other words, the main contribution of this work is to explore the benefits of centrality-based caching methods in SBSs scenario, where a simplified content dissemination process in social networks is detailed additionally.

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A. System Model

Consider a social network formed by N users, represented by a graph $\mathcal{G} = (\mathcal{N}, \mathcal{E})$ where \mathcal{N} is the set of nodes (or users) and \mathcal{E} is the set of edges (or social links). In this social network, a subset $\mathcal{N}' \subset \mathcal{N}$ of N' users is considered as a socio-technical network as shown in Fig. 1. The socio-technical network (including the mobile wireless network) consists of a cache-enabled SBS that serves these N' users via wireless links with total capacity of C_w . To achieve this, a central scheduler is in charge of providing broadband Internet connection to this SBS via a capacity-limited backhaul link with capacity C_b . Depending on whether the requested content is in the cache or not, the SBS can either bring the content from the Internet via the backhaul link or serve the requesting user from its local cache. In such a scenario, offloading the technological infrastructure (reducing backhaul usage) depends on how smartly the network is able to put (or remove) the content in the cache of an SBS before (or during) the requests are being served.

Clearly, as these N' users are part of the socio-technical network, analyzing the interactions in the social network (content viewing or/and publishing of users over the time) can help the SBS to maximize the benefits from content caching, in terms of improved offload and reduced access delay. In this respect, we assume that there exists F unique contents in a catalog, where the length of each content is denoted by L . For simplicity, we assume that each user in the social network owns only one type of unique content, thus $N = F^1$. Let \mathcal{R} be the set of R requests that are chosen from this catalog and performed during T time steps. For the SBS, we define a *cache indicator* vector $\Theta \in \{0, 1\}^{1 \times F}$ in the SBS where $\theta_f = 1$ implies that f -th content is cached and $\theta_f = 0$ otherwise. We also assume that Θ is fixed during this time period. Then, the maximization of backhaul *offloading gain* can be formally given by:

$$\begin{aligned} & \underset{\Theta}{\text{maximize}} && \frac{1}{R} \sum_{r \in \mathcal{R}} \mathbb{1}\{\theta_{f_r}\}, \\ & \text{subject to} && \Theta \Theta^T \leq \frac{S}{L}. \end{aligned} \quad (1)$$

where f_r is the requested content, $\mathbb{1}\{\cdot\}$ is the indicator function, and S is the storage capacity of the SBS. If the content request pattern is perfectly known by the SBS, the most reasonable offline caching approach for obtaining the

¹The relaxation of $N = F$ may introduce additional analysis but can be an interesting work to reveal.

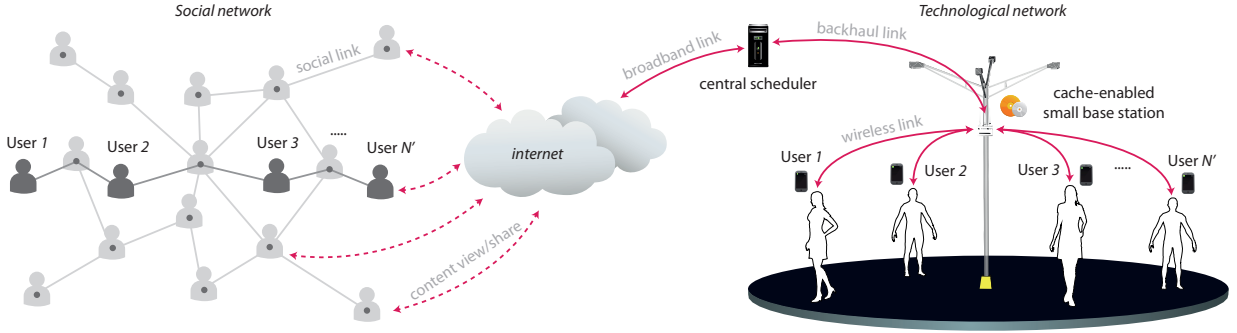


Figure 1: An illustration of the scenario. The dark gray users in the social network are part of the socio-technical network.

solution of (1) is to store the most popular content under given storage constraints. However, this requires the perfect knowledge on the content popularity within the social network which may not be known in the SBS, as discussed next.

B. Content Dissemination in Social Network

In a social network, each user has its own content to view and publish (or share), and also can view and publish other users' content. Once a content is published at a time step, the friends of publishing user will receive a notification of content which will subsequently allow them to view and publish at the next time step with some given probability. Although this process continues over time, the occurrence of view and publish events will clearly depend on the corresponding probabilities and the structure of the social network.

Let $\mathbf{V}[t] \in \mathbb{N}^{N \times F}$ be the *view history matrix* representing the number of content views by users, where the entry $v_{u,f}^t$ corresponds to the number of views by user u for content f up to time t . Similarly, let $\mathbf{S}[t] \in \mathbb{N}^{N \times F}$ be the *sharing history matrix* which represents the number of content shares by users, where $s_{u,f}^t$ is the entry of user u for content f up to time t .

In the content dissemination process, each user is initially interested to share its own content. More precisely, at time t , assume that a set of users are publishing (and viewing at the same time) their content with probability p_{pub} . Let $X \sim \text{Uniform}(0, 1)$ be a random variable. Then, the entries of $\mathbf{V}[t]$ and $\mathbf{S}[t]$ initially take values as follows:

$$v_{u,f}^t = s_{u,f}^t = \begin{cases} 1 & \text{if } X \leq p_{\text{pub}}, \\ 0 & \text{otherwise.} \end{cases}$$

Once a set of content is initially published by a user with probability p_{pub} , both this user and its friends will receive notifications. In this case, we assume that they can decide to either view the published content or not in the next time step. Thus, the probability of user u viewing the notified content f is defined as

$$p_{\text{view}}^{t+1}(u, f) = \begin{cases} \frac{\alpha}{1 + \eta v_{u,f}^t} & \text{if } u = f, \\ \frac{\alpha}{1 + \eta' v_{u,f}^t} & \text{otherwise,} \end{cases}$$

where $0 \leq \alpha \leq 1$ is a constant for view probability, $\eta \geq 0$ is the decay factor for probability of viewing its own notified content and $\eta' \geq 0$ is the decay factor of viewing non-owned notified content. We assume that $\eta > \eta'$ holds so that the

probability of viewing its own content ($u = f$) decays faster than the probability of viewing non-owned content ($u \neq f$). According to the given time varying view probability p_{view}^{t+1} , the view history matrix $\mathbf{V}[t+1]$ takes the values as follows:

$$v_{u,f}^{t+1} = \begin{cases} v_{u,f}^t + 1 & \text{if } X \leq p_{\text{view}}^{t+1}(u, f), \\ v_{u,f}^t & \text{otherwise.} \end{cases}$$

After a notified content f is viewed by user u at time $t+1$, we suppose that this user shares the content at the same time slot $t+1$ according to the probability defined as follows:

$$p_{\text{share}}^{t+1}(u, f) = \begin{cases} \frac{\beta}{1 + \kappa v_{u,f}^t} & \text{if } u = f, \\ \frac{\beta}{1 + \kappa' v_{u,f}^t} & \text{otherwise,} \end{cases}$$

where $0 \leq \beta \leq 1$ is a constant for share probability, $\kappa \geq 0$ is the decay factor for probability of sharing his/her own viewed content and $\kappa' \geq 0$ is for the probability of sharing non-owned viewed content. Thus, the share history matrix takes values as follows:

$$s_{u,f}^{t+1} = \begin{cases} s_{u,f}^t + 1 & \text{if } X \leq p_{\text{share}}^{t+1}(u, f), \\ s_{u,f}^t & \text{otherwise.} \end{cases}$$

This is the stochastic content dissemination process in the social network. In this work, we assume that the dynamics of this process are not known at the SBS in practice (thus the change of popularity over time is not known). We will only consider such a knowledge in the numerical setup for comparison purposes with the centrality-based caching approaches given in the next.

C. Centrality-based Content Caching

Since the topology of the social network has a high impact on content dissemination, exploiting this knowledge (i.e., by detecting influential users of the social network and caching their content in the SBS accordingly) can improve the cache-hit rates, thus yielding non-negligible offloading gains.

Indeed, quantifying the social network structure can be done with various metrics with the most popular being the notion of centrality [6]. A node's centrality is a way to measure the total influence of this node within a social structure. Given the broad definition of influence, there exists a variety of social centrality measures each of which having its own properties, as follows:

- *Degree centrality* is the simplest measure of centrality in which the number of direct social and friendship links of a user determine its influence.
- *Closeness centrality* quantifies the influence of a user via its mean distance to other nearby users.
- *Betweenness centrality* measures the extent to which a user lies on paths connecting other users in the social graph.
- *Eigenvector centrality* which is estimated via the eigenvalue decomposition of the adjacency matrix of the network, where the eigenvector corresponding to the largest eigenvalue quantifies the centrality of these users.

In what follows, we provide numerical results of the scenario given above.

II. NUMERICAL RESULTS AND DISCUSSIONS

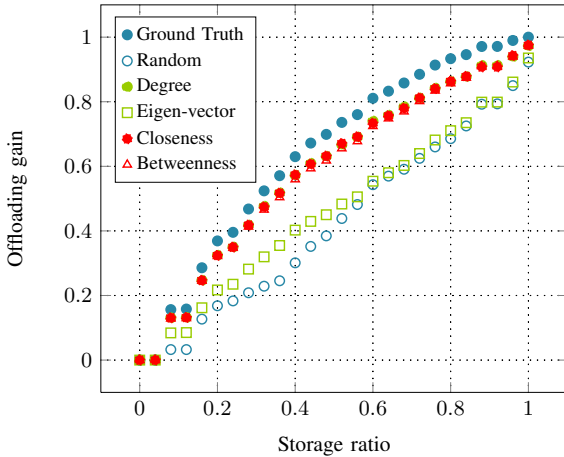


Figure 2: Evolution of the offloading with respect to the storage size. The social link attach rate is 3, $N' = 16$, $F = 16$, $L = 1$ Mb, $C_b = 8$ Mbps, $C_w = 128$ Mbps, $p_{\text{pub}} = 0.8$, $\alpha = 0.6$, $\eta = 10$, $\eta' = 1$, $\beta = 0.4$, $\kappa = 100$, $\kappa' = 10$.

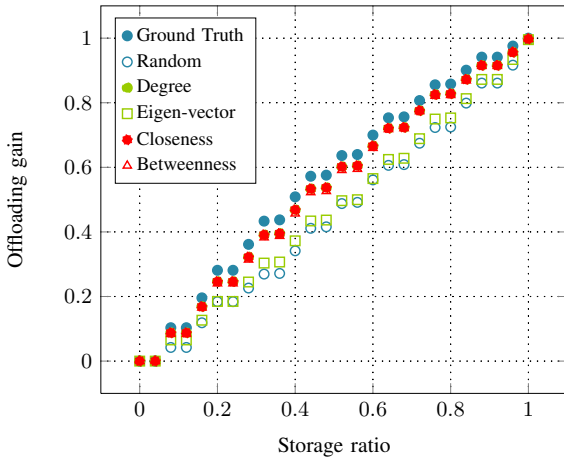


Figure 3: Evolution of the offloading gain with respect to the storage ratio. The social link attach rate is 7 whereas the rest of setup parameters is identical to the setup studied in Fig. 2.

In our simulation setup, for ease of exposition, we assume that the considered social network is the only contributor to the

global traffic. In other words, there are no other traffic sources observed in the SBS. Statistical simulation results are averaged over a large number of independent runs. The preferential attachment (PA) model [6] is used for social network generation. Given this social network, the content dissemination process is executed for 16 time slots. As far as the cache decision using centrality measures is concerned, the content of users are stored starting from the most influential user to least influential one until no storage size remains. The following caching policies are used for comparison purposes: 1) *Ground truth*: Users' most popular content is stored according to the fully known view history matrix $\mathbf{V}[t]$ and 2) *Random*: Caching is done uniformly at random, regardless of any statistics of the content dissemination and structure of the social network.

Fig. 2 shows the evolution of backhaul offloading gain as a function of the storage ratio for the case which the social link attach rate is 3 (see PA model [6] for details). In Fig. 2, we can see that, according to this setup, the closeness and betweenness measures perform closely to the ground truth, whereas the eigen-vector centrality has poor performance that is close to the random approach.

Fig. 3 illustrates the change of backhaul offloading gain with respect to the storage ratio in the case where the social link attach rate is 7. Since the number of social links per user is higher compared to the case shown in Fig. 2, the interactions in the content dissemination increase, yielding higher load on the SBS. Therefore, due to this high load, performance gap, in terms of offloading gain become closer compared to the setting in Fig. 2, even though the insights are identical.

III. CONCLUSIONS

In this short abstract, we have studied the usage of centrality measures for caching decision where the complete information of content dissemination in social network is not known at the network's base stations. Our preliminary results have shown that reasonable offloading gains can be obtained by using these metrics. Several future directions can be foreseen. On the one hand, the impact of scenario parameters on the performance can be revealed in details. On the other hand, a more rigorous analysis of the content dissemination in social networks can be conducted.

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